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Investigating the effects of multiple exposure measures to traffic-related air pollution on the risk of breast and prostate cancer

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A B S T R A C T

Traffic-related nitrogen dioxide (NO_2) has been traditionally estimated using surfaces generated through land-use regression (LUR). Recently, air pollution dispersion has been used to derive NO_2 exposures in urban areas. There is evidence that data collection protocols and modelling assumptions can have a large effect on the resulting NO_2 spatial distribution. This study investigates the effects of various NO_2 surfaces on the risk estimates of postmenopausal breast cancer (BC) and prostate cancer (PC), both of which have already been associated with traffic-related air pollution. We derived exposures for individuals in two case control studies in Montreal, Canada using four different surfaces for NO_2. Two of the surfaces were developed using LUR but employed different data collection protocols (LUR-1 and LUR-2), and the other two surfaces were generated using dispersion modelling; one with a regional model (dispersion-1) and another with a street canyon model (dispersion-2). Also, we estimated separate odds ratios (ORs) using concentrations of NO_2 as measures of exposure for both cancers. While the range of NO_2 concentrations from dispersion (4–26 ppb) was lower than the range from LUR (4–36 ppb), the four surfaces were found to be moderately correlated, with Spearman correlation coefficients ranging from 0.76 to 0.88. The ORs for BC were estimated to be 1.26, 1.10, 1.07, and 1.05 based on LUR-1, LUR-2, dispersion-1, and dispersion-2. In contrast, the ORs for PC were estimated to be 1.39, 1.30, 1.13, and 1.04 based on LUR-1, LUR-2, dispersion-1, and dispersion-2. The four exposure measures indicated positive associations but we observed higher mean ORs based on the LUR surfaces albeit with overlapping CIs. Since LUR models capture all sources of NO_2 and dispersion models only capture traffic emissions, it is possible that this difference is due to the fact that non-road sources also contribute to the spatial distribution in NO_2 concentrations.

1. Introduction

In urban areas, emissions from traffic constitute the main air pollution source. A wide range of studies have linked exposure to

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traffic-related air pollution with increased incidence of asthma (Carlsten et al. 2010; Gehring et al. 2010; Snowden et al. 2014), ischemic heart disease (Gan et al. 2011; Nyhan et al. 2014; Weichenthal et al. 2011), neurodegenerative diseases (Levesque et al. 2011; Wang et al. 2009), and various forms of cancer such as breast cancer (Crouse et al. 2010), prostate cancer (Parent et al. 2013), and lung cancer (Hamra et al. 2015). In particular, exposure to nitrogen dioxide (NO_2), an accepted marker of traffic-related air pollution, has been associated with various health outcomes. For example, Chen et al. (2013) showed that a 5 ppb increase in NO_2 exposure was associated with a 12% increase in the risk of mortality from cardiovascular disease. In a lung cancer study, Hamra et al. (2015) estimated that a 10 $\mu g/m^3$ increase in exposure to NO_2 was associated with a 4% increase in the risk of lung cancer. In another study of chronic obstructive pulmonary disease (COPD) conducted among 52,799 participants, the authors estimated that an increase in the 35-year mean NO_2 level by 5.8 $\mu g/m^3$ was associated with an increased risk of COPD by 8% (Andersen et al., 2011).

Traditionally, NO_2 exposure surfaces have been developed using land-use regression (LUR) models, whereby integrated NO_2 measurements were conducted with passive samplers. Then, exposures were modelled at the home location of study participants (Abernethy et al. 2013; Beelen et al. 2013; Dons et al. 2014; Hoek et al. 2008; Lee et al. 2014; Shekarrizfard et al. 2015). With advances in air pollution instrumentation and improved knowledge of travel and activity patterns of individuals in urban areas, new methods of deriving exposure have become possible. For example, the development of NO_2 sensors has enabled the implementation of short-term monitoring campaigns (Austin et al. 2006; Deville Cavellin et al. 2016; Setton et al. 2011) and personal measurements (Mcadam et al., 2011; Pattinson et al. 2014) while improvements in travel demand forecasting and traffic modelling motivated the development of traffic emission and dispersion models, capable of capturing the spatio-temporal variability in air pollution within urban areas (Beckx et al. 2009; Hatzopoulou and Miller 2010; Shekarrizfard et al. 2017). LUR modelling necessitates the deployment of large air quality sampling campaigns with extensive spatial and temporal coverage (Beelen et al. 2013; Lee et al. 2014; Levy et al. 2010).

As an alternative to statistical techniques, dispersion modelling involves constructing a dynamic model of the dispersion processes occurring at the intra-urban scale. In this context, dispersion models capable of simulating air quality at the level of individual roads are grouped into 3 main categories: 1) Gaussian dispersion models, which are typically used for areas without obstacles or with obstacles of simple geometry; these models can be accurate at the top of the urban canopy and are mainly Gaussian plume and Gaussian puff models (Cimorelli et al. 2005; Scire et al. 2000); 2) Street-canyon models, which are appropriate for cities with tall buildings; they simulate pollutant transfer along the street and at intersections (Hertel and Berkowicz 1989; Soulhac et al. 2011); and 3) Computational Fluid Dynamics (CFD) models; they provide detailed representations of the atmospheric flow and some also treat the physics and chemistry of air pollutant transformations; they are however limited to local applications such as the impact of a single pollution source in complex street geometry and flow characteristics (Eichhorn and Kniffka 2010; Milliez and Carissimo 2007). Dispersion modelling of road traffic sources has been conducted for a variety of road and network configurations (Batterman et al. 2010; Hatzopoulou and Miller 2010; Lee et al. 2009; Ning et al. 2005; Sangkapichai et al. 2010). Output from dispersion models has been used in previous epidemiologic studies (Bellander et al. 2001; Gauderman et al., (2005); Henderson. et al., 2011; Nafstad et al. 2003; Raaschou-Nielsen et al. 2010). For example, in a 27-year follow-up study, Nafstad et al. (2003) estimated NO_2 concentrations using sets of dispersion field coefficients given from model calculations for each year. The authors estimated 8% increase in the risk of lung cancer (95% CI: 1.02–1.15) for a 10 $\mu g/m^3$ increase in NO_2 at the home address. Gauderman et al., (2005) used the CALINE4 dispersion model to estimate traffic-related NO_x and estimated that with an increase in NO_2 concentrations by 5.7 ppb, the odds ratio (OR) for childhood asthma was 1.83 (95% CI: 1.04–3.21). Raaschou-Nielsen et al. (2010) used the OSPM dispersion model to estimate traffic related NO_x concentrations and estimated that the incidence rate ratios for lung cancer were 1.30 (95% CI: 1.07–1.57) and 1.45 (95% CI, 1.12–1.88) for NO_x concentrations of 30–72 $\mu g/m^3$ and greater than 72 $\mu g/m^3$, respectively. Furthermore, in a case-control study of stillbirths, Ihrig et al. (1998) estimated arsenic exposure levels from airborne emissions using a dust dispersion model in Texas and the OR observed for Hispanics in the high exposure group ($> 100 \mu g/m^3$ arsenic) was 8.4. Henderson. et al., (2011) estimated smoke-related PM_{10} from the CALPUFF dispersion model and estimated the ORs for a 30 $\mu g/m^3$ increase in tapered element oscillating microbalance (TEOM)-based PM_{10} to be equal to 1.05 (95% CI: 1.03–1.06) for all respiratory physician visits, 1.16 (95% CI: 1.09–1.23) for asthma-specific visits, and 1.15 (95% CI: 1.00–1.29) for respiratory hospital admissions. Finally, Bellander et al. (2001) estimated NO_2 concentrations using the AIRVIRO dispersion model for all years spanning between 1955 and 1990 for the entire Stockholm area and assigned the NO_2 exposures to 10,800 geocoded addresses. They concluded that while this technique has practical applications for epidemiological studies, it might be limited to study sites that possessed historical traffic and other emission data.

The main strength of LUR is the use of monitoring data and the relative ease of model development. Dispersion models have the advantage of incorporating both spatial and temporal variation of air pollution within a study area and can be applied at different spatial scales. Some of the limitations of these models include the assumptions about dispersion patterns (e.g., Gaussian dispersion), the need for validation against monitoring stations, and relatively costly meteorological and emission data inputs (Jerrett et al. 2005). A number of studies have compared the performance of LUR and dispersion modelling (Bell 2006; Briggs et al. 2000; Briggs et al. 1997; Cyrys et al. 2005; Dijkema et al. 2011; Hennig et al. 2016; Jerrett et al. 2005; Marshall et al. 2008; Wu et al. 2011). These studies suggest that LUR models can explain the small-scale variations in air pollution concentrations as well or even better than most dispersion models. Results, however, depend on the characteristics of the study area, the density of the monitoring, and the resolution of the predictor variables. Beelen et al. (2010) compared the performance of high-resolution LUR and dispersion models in estimating small-scale variations in NO_2 concentrations and observed a moderate agreement between the estimated concentrations based on the two methods. The dispersion model performed better than the LUR model with a correlation of 0.77 versus 0.47 against data from fixed stations. Marshall et al. (2008) used three approaches for estimating within-urban spatio-temporal variability in ambient concentrations: (a) spatial interpolation of monitoring data (nearest and inverse distance weighted (IDW)), (b) LUR, and (c) a